BODHIVRUKSHA JOURNAL OF DIVERSE DISCIPLINE
E-ISSN : 3139-1486
An Open Access, Peer-Reviewed, Multidisciplinary Scholarly Journal
Bi-monthly | Multilingual (English, Hindi, Marathi) | Academic Research
@ Volume 2, Issue 5 (September-October 2026) (Special Issue 1) ISSN: 3139-1486 (Online)

AIoT-Based Smart Classroom Energy Optimization and Occupancy Monitoring System

Amruta Sangtani
Ajeenkya DY Patil School of Engineering
Pune, Maharashtra, India
Academic Year: 2026–2027
Email: amruta.sangtani@dypic.in

Bhakti Gore
Ajeenkya DY Patil School of Engineering
Pune, Maharashtra, India
Academic Year: 2026–2027
Email: bhakti.gore@dypic.in

Akanksha Yelmate
Ajeenkya DY Patil School of Engineering
Pune, Maharashtra, India
Academic Year: 2026–2027
Email: akanksha.yelmate@dypic.in

Dr. Vishal Puranik
Guide
Ajeenkya DY Patil School of Engineering
Pune, Maharashtra, India
Email: vishal.puranik@dypic.in

Abstract

Lights and fans in many classrooms keep running after the last student has left, or while daylight is already enough, which raises electricity bills for no benefit. Earlier smart-building studies usually either measure energy or switch appliances, and few of them join occupancy sensing, a learned decision model and an inexpensive working prototype. This paper describes an AIoT prototype for a laboratory-scale classroom. An ESP32 board reads IR seat sensors, an LDR and a DHT22 sensor, and a Random Forest classifier, trained on 1,050 cleaned records with an 80:20 split, predicts whether the light and the fan should be on. The model reached 96.2% accuracy on the held-out data, with precision and recall between 94.3% and 95.8%, and fixed thresholds (light level ≤ 250, temperature ≥ 28 °C) keep the behaviour predictable. The

BODHIVRUKSHA JOURNAL OF DIVERSE DISCIPLINE
E-ISSN : 3139-1486
An Open Access, Peer-Reviewed, Multidisciplinary Scholarly Journal
Bi-monthly | Multilingual (English, Hindi, Marathi) | Academic Research
@ Volume 2, Issue 5 (September-October 2026) (Special Issue 1) ISSN: 3139-1486 (Online)

circuit was simulated on the Velxio platform, the prototype was demonstrated at the project exhibition on 17 October 2026, and its approximate cost is Rs. 1,960. Comparing always-on operation with controlled operation suggests savings of roughly 40–60%, but this is an estimate that still needs metered confirmation.

Keywords: AIoT, Smart Classroom, Occupancy Monitoring, Energy Optimization, ESP32, Random Forest, Internet of Things.

Introduction

Lighting, fans and cooling account for much of the electricity used by schools and colleges, and a good share is lost when appliances are left running in empty or brightly lit rooms. Switching by hand depends on people remembering to do it, and most institutions hold no record showing how a particular room is actually used. Low-cost IoT hardware and compact machine-learning models now make it practical to observe a room continuously and let a controller switch appliances only when they are needed.

Artificial Intelligence of Things (AIoT) joins IoT sensing and connectivity with AI-based analysis. In the classroom prototype studied here, IR sensors show which seats are taken, an LDR reports the light level, and a DHT22 gives temperature and humidity. An ESP32 reads these values, drives a relay-switched fan and an LED, shows the status on a 0.96-inch OLED and appends every reading to a CSV file, while a Random Forest model supplies the ON/OFF decision.

Work published between 2024 and 2026 applies machine learning, deep learning and reinforcement learning to classroom energy prediction, occupancy estimation and the control of lighting and air conditioning [1]–[20]. Related trends include edge computing on inexpensive microcontrollers for fast local control, cloud dashboards for remote monitoring, and sustainability targets that aim to shrink the carbon footprint of buildings. The privacy of occupancy data, for example through encrypted transmission and role-based access, is also receiving attention.

The contributions of this paper are: (i) a review of twenty recent studies and the gap they leave; (ii) a five-layer, low-cost architecture that combines occupancy sensing, learned decisions, automatic control, display and logging; (iii) a Random Forest model with threshold logic for light and fan control, evaluated with accuracy, precision and recall; and (iv) a simulation, a working prototype and a cost analysis. The paper is organised as follows: the Related Work section reviews the literature, the Problem Statement and Objectives section states the problem, the Proposed System Architecture and Methodology sections present the design, the Implementation and Results section reports the findings, and the remaining sections cover discussion, ethical and sustainability aspects, and the conclusion with future scope.

Related Work

A. Search Strategy

Candidate papers came from ScienceDirect, Scientific Reports, MDPI, Frontiers and Google Scholar, searched with terms like smart classroom energy, machine-learning occupancy detection, IoT energy monitoring for educational buildings and classroom energy prediction. We kept twenty studies from 2024–2026 dealing with energy prediction, occupancy estimation or smart control in educational buildings and dropped anything outside that setting.

BODHIVRUKSHA JOURNAL OF DIVERSE DISCIPLINE
E-ISSN : 3139-1486
An Open Access, Peer-Reviewed, Multidisciplinary Scholarly Journal
Bi-monthly | Multilingual (English, Hindi, Marathi) | Academic Research
@ Volume 2, Issue 5 (September-October 2026) (Special Issue 1) ISSN: 3139-1486 (Online)

B. Energy Prediction

The first group of studies forecasts consumption. Random Forest, gradient boosting, LSTM and DNN models were compared on educational-building data in [1], [15] and [16], and classroom-level work found that student count and climate variables matter for prediction [10], [11]. Campus-scale forecasting with behavioural data [13], prediction of thermal and visual comfort [18], efficiency studies that also consider indoor air quality [9] and long-term prediction with optimized AI models [20] extend this line. These works are strong on prediction but do not close the loop by switching appliances in a small room.

C. Occupancy Estimation and Control

The second group estimates how many people are present and uses the estimate for control. Environmental sensor streams can reveal occupancy without intrusive devices [17]; deep models such as a Mamba-based predictor [5] and multi-objective optimizers [7] support HVAC and energy decisions; and vision-based systems have been applied to air-conditioning control and comfort optimization [6], [19]. Cameras raise privacy concerns and need more infrastructure, and the advanced models are heavy for a microcontroller.

D. IoT Monitoring and Control Systems

The third group builds working systems: an embedded smart classroom with attendance, power metering and automatic lighting [2]; AI-assisted classroom monitoring for space utilization [3]; lecture-room occupancy and energy monitoring [12]; and BIM/IIoT or reinforcement-learning energy management [4], [8]. A systematic review reports that integrating smart energy systems with occupant behaviour remains difficult [14].

E. Comparison and Research Gap

Table 1: Summary of the reviewed literature by theme

Theme	Works	Observed limitation
Energy prediction	[1], [9]–[11], [13], [15], [16], [18], [20]	Building- or campus-level forecasts; seldom a real-time controller
Occupancy estimation	[5]–[7], [17], [19]	Vision or deep models; camera needs and high computation
IoT monitoring and control	[2]–[4], [8], [12]	Heavy infrastructure, or no central AI component [12]
Systematic review	[14]	Review only; no prototype or model

Taken together, existing systems mostly either monitor energy or control appliances; few combine occupancy detection with AI-based prediction, real-time sensor-plus-ML integration for classrooms is limited, and low-cost optimization of lights and fans with logging is rarely offered in one package. Tree-based models such as Random Forest suit small tabular sensor data and gave good results on classroom energy tasks [11], [15], [18], while IR seat sensors are cheap and capture no images. This motivates an integrated, low-cost prototype that unites IoT sensing, ML-based decisions, automatic relay control and live monitoring.

BODHIVRUKSHA JOURNAL OF DIVERSE DISCIPLINE
E-ISSN : 3139-1486
An Open Access, Peer-Reviewed, Multidisciplinary Scholarly Journal
Bi-monthly | Multilingual (English, Hindi, Marathi) | Academic Research
@ Volume 2, Issue 5 (September-October 2026) (Special Issue 1) ISSN: 3139-1486 (Online)

Problem Statement and Objectives

Problem. The aim is to design an AIoT-based smart classroom system that uses live sensor data and machine learning to detect how many students are present, monitor environmental conditions and optimize energy use, so that waste is reduced while the room stays comfortable and the learning environment sustainable.

Objectives. The work sets out (1) to monitor occupancy with IR sensors; (2) to measure temperature, humidity and light intensity with a DHT sensor and an LDR; (3) to clean the collected data and train a Random Forest on it; (4) to predict the ON/OFF state of the light and fan from occupancy, temperature, humidity and light level; (5) to drive an LED and a DC fan through the ESP32 and a relay; (6) to show readings on an OLED and allow remote monitoring through an IoT dashboard; (7) to evaluate the model with accuracy, precision and recall; and (8) to promote energy-efficient operation through occupancy-aware control.

Scope. The study stays at laboratory scale: it designs, simulates and builds the prototype, but leaves out a live classroom installation, air conditioners and other mains loads, multi-room roll-out and long-duration measurement of real savings.

Proposed System Architecture

Fig. 1 arranges the design into five tiers. Sensors feed an ESP32-centred processing tier; a decision tier holding the learned model sends commands to an actuator and display tier; and a monitoring tier records the data and can serve a web dashboard through Wi-Fi.

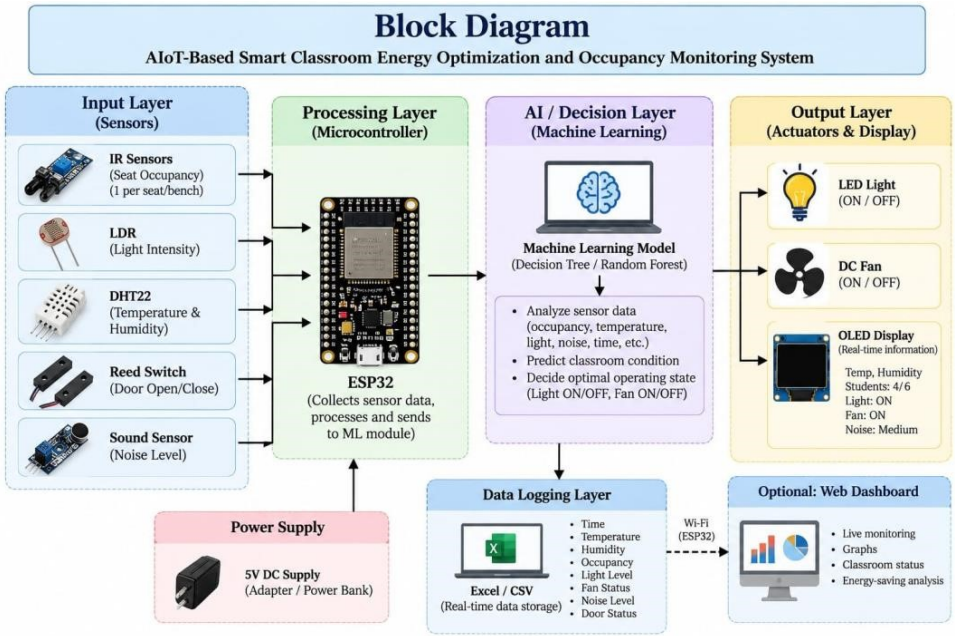


Fig. 1. Block diagram of the proposed AIoT-based smart classroom system.

BODHIVRUKSHA JOURNAL OF DIVERSE DISCIPLINE
E-ISSN : 3139-1486
An Open Access, Peer-Reviewed, Multidisciplinary Scholarly Journal
Bi-monthly | Multilingual (English, Hindi, Marathi) | Academic Research
@ Volume 2, Issue 5 (September-October 2026) (Special Issue 1) ISSN: 3139-1486 (Online)

A. Layers

Input layer. Each seat or bench carries an IR sensor for occupancy, while the LDR supplies the light level and the DHT22 supplies temperature and humidity. The proposed design also lists a reed switch for the door and a sound sensor for noise. **Processing layer.** The ESP32 DevKit V1 collects these readings and hands them to the model. **AI/decision layer.** A Decision Tree or Random Forest picks the best operating state for the light and fan. **Output layer.** The LED and the 5 V DC fan (via a relay module) are switched, and the OLED presents live data. **Monitoring layer.** Each record, with time, climate values, occupancy, device states, noise and door status, is stored in an Excel/CSV file. A 5 V adapter or power bank powers everything.

B. Working Principle

The prototype works in seven steps. (1) *Sensing:* the IR sensors, LDR, DHT22 and the optional door and sound sensors collect data continuously. (2) *Processing:* the ESP32 reads occupancy, light, temperature, humidity, noise and door status. (3) *Decision:* the model classifies the room condition and chooses the operating state of the light and fan. (4) *Control:* with students present and low light, the light and fan are switched on; with an empty room or sufficient light they are switched off. (5) *Display:* the OLED shows temperature, humidity, the student count (for example 4/6), and the light, fan and noise status. (6) *Logging:* all readings and device states are stored in CSV/Excel. (7) *Analysis:* estimated consumption is compared with an always-on classroom to show the saving.

C. Hardware and Wiring

The prototype uses an ESP32 DevKit V1, six IR sensor modules, an LDR, a DHT22, a reed switch, a sound sensor, a 0.96-inch OLED, 5 V relay modules, a 5 V DC fan, an LED, a breadboard and jumper wires. Software tools are the Arduino IDE, the Velxio simulator, and Python with scikit-learn. Table 2 lists the pin mapping used in Fig. 2.

BODHIVRUKSHA JOURNAL OF DIVERSE DISCIPLINE
E-ISSN : 3139-1486
An Open Access, Peer-Reviewed, Multidisciplinary Scholarly Journal
Bi-monthly | Multilingual (English, Hindi, Marathi) | Academic Research
@ Volume 2, Issue 5 (September-October 2026) (Special Issue 1) ISSN: 3139-1486 (Online)

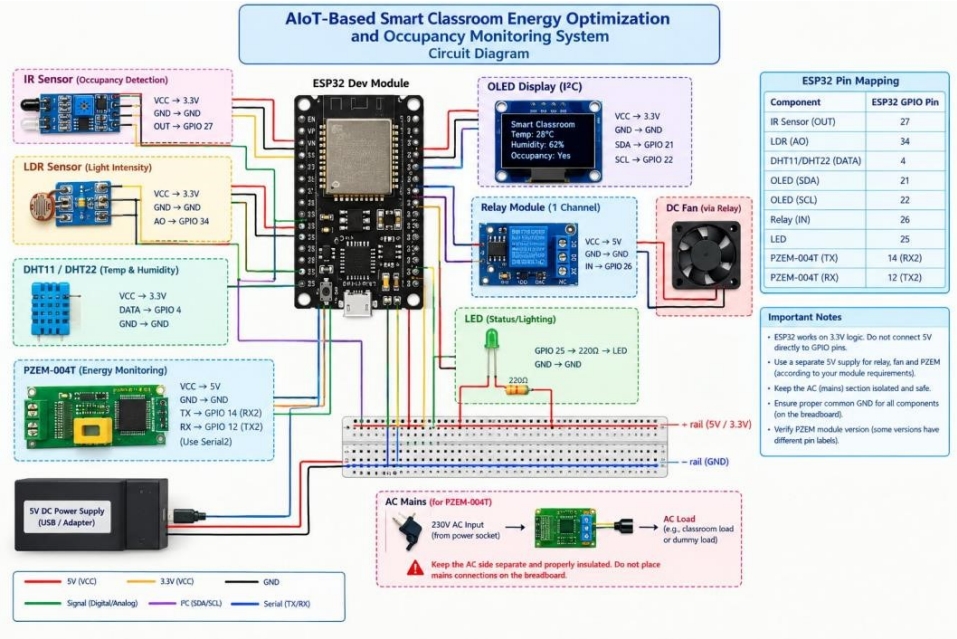


Fig. 2. Circuit diagram of the prototype with the ESP32 pin connections.

Table 2: ESP32 pin mapping

Device	Device pin	ESP32 pin
IR sensor	OUT	GPIO 27
LDR sensor	AO	GPIO 34
DHT11 / DHT22	DATA	GPIO 4
OLED display (I²C)	SDA / SCL	GPIO 21 / GPIO 22
Relay module (1 channel)	IN	GPIO 26
LED (through 220 Ω)	Anode	GPIO 25
PZEM-004T	TX / RX	GPIO 14 / GPIO 12

Because the ESP32 GPIO pins tolerate only 3.3 V, no 5 V line may be connected to them directly. The relay, fan and PZEM module therefore take power from a separate 5 V source that shares a ground with the board. Any mains wiring for the PZEM-004T energy meter must be insulated and kept apart from the breadboard.

Methodology

A. Development Stages

Development proceeded through eight steps: studying the problem and the literature; choosing sensors and parts; designing and simulating the circuit on Velxio; writing the ESP32 firmware for sensing, thresholds, display and relay control; preparing the classroom dataset; training and testing the Random Forest; building the breadboard prototype on a 5 V supply; and finally integrating, testing and analysing everything together.

BODHIVRUKSHA JOURNAL OF DIVERSE DISCIPLINE
E-ISSN : 3139-1486
An Open Access, Peer-Reviewed, Multidisciplinary Scholarly Journal
Bi-monthly | Multilingual (English, Hindi, Marathi) | Academic Research
@ Volume 2, Issue 5 (September-October 2026) (Special Issue 1) ISSN: 3139-1486 (Online)

B. Dataset and Preprocessing

The cleaned dataset contains 1,050 records. Missing values were handled, Yes/No fields were encoded as 1/0 and numerical features were scaled. Temperature, humidity, light level and student presence form the input vector, and the LED and fan states are the outputs. The data were divided into 80% for training and 20% for testing.

C. Random Forest Model and Metrics

A Random Forest is an ensemble of decision trees, each grown on a random sample of the data. The final class is the majority vote of the trees, which limits over-fitting and works well on small tabular sensor datasets:

$$\hat{y} = \text{mode}\{h_1(x), h_2(x), \ldots, h_N(x)\} \tag{1}$$

Here x stands for the feature vector (temperature, humidity, light level and student presence), $h_t(x)$ is the vote of tree t on the LED or fan state, and $\hat{y}$ is the resulting ON/OFF prediction. Model quality is judged with

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

with TP, TN, FP and FN denoting true positives, true negatives, false positives and false negatives. The relative energy saving over a common period is

$$S(\%) = \frac{E_{\text{ON}} - E_{\text{AIoT}}}{E_{\text{ON}}} \times 100 \tag{4}$$

where E_{ON} is the appliance energy of an always-on room and E_{AIoT} that of the AIoT-controlled room.

D. Threshold Logic and Control Algorithm

Fixed thresholds support the model and make the response easy to predict (Table 3). Algorithm 1 gives the resulting control loop.

Table 3: Threshold values used in the code

Parameter	Threshold	Condition	Action
Light (LDR)	≤ 250	Dark	LED ON
Temperature	≥ 28 °C	High	Fan ON
Student presence	> 0	Occupied	Use model prediction
Humidity	monitoring only	—	Model feature

BODHIVRUKSHA JOURNAL OF DIVERSE DISCIPLINE
E-ISSN : 3139-1486
An Open Access, Peer-Reviewed, Multidisciplinary Scholarly Journal
Bi-monthly | Multilingual (English, Hindi, Marathi) | Academic Research
@ Volume 2, Issue 5 (September-October 2026) (Special Issue 1) ISSN: 3139-1486 (Online)

Algorithm 1: Occupancy-based appliance control

Input: DHT22, LDR and IR sensor readings; trained Random Forest.

1. Read temperature T and humidity H from the DHT22, light level L from the LDR and seat states from the IR sensors.
2. Count occupied seats n; set present = true if $n > 0$.
3. If present and $L \leq 250$, set ledRequired = true.
4. If present and $T \geq 28.0$ °C, set fanRequired = true.
5. Give (T, H, L, presence) to the Random Forest to predict the LED and fan states.
6. Drive the LED and the fan relay accordingly; switch both OFF when the room is empty or light is sufficient.
7. Show the status on the OLED, append a record to the CSV log and repeat from step 1.

Implementation and Results

A. Circuit Simulation

The Velxio online simulator hosted the virtual build (Fig. 3): an ESP32 DevKit V1 with a DHT22, an LDR module, an SSD1306 OLED, a relay for the DC fan, an LED behind a series resistor and a microSD module for CSV logging. At start-up the OLED displays “SMART CLASS” and “Demo Starting...”, and the serial monitor (115200 baud) prints “SMART CLASSROOM CSV DEMO” followed by the number of records and the fan and LED states.

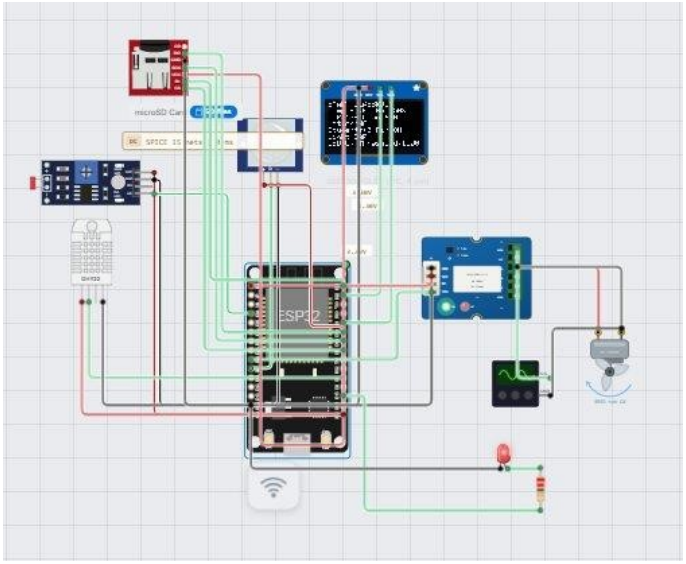


Fig. 3. Circuit simulation on the Velxio platform.

BODHIVRUKSHA JOURNAL OF DIVERSE DISCIPLINE
E-ISSN : 3139-1486
An Open Access, Peer-Reviewed, Multidisciplinary Scholarly Journal
Bi-monthly | Multilingual (English, Hindi, Marathi) | Academic Research
@ Volume 2, Issue 5 (September-October 2026) (Special Issue 1) ISSN: 3139-1486 (Online)

B. Prototype and Exhibition

Fig. 4 shows the prototype: the ESP32 and its sensors sit on a breadboard in a transparent box beside a DC fan. It was presented, together with the poster, to the guide and evaluators at the project exhibition held on 17 October 2026 at the college campus in Charholi Budruk, Pimpri-Chinchwad, while the simulation ran live on a laptop.

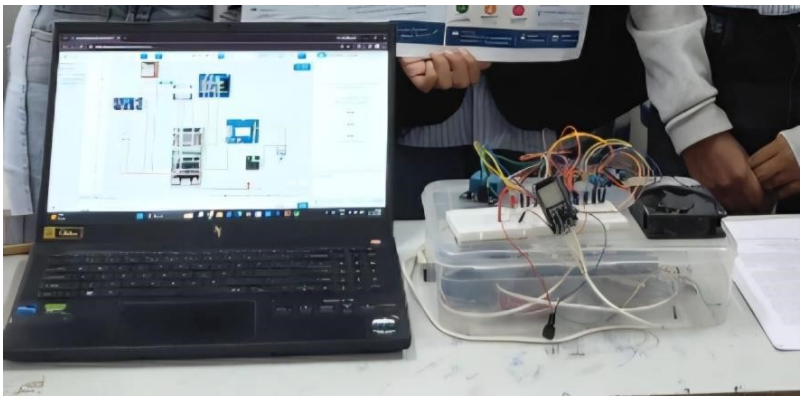


Fig. 4. Working prototype with the live simulation.

C. Model Performance

Table 4 gives the results on the test portion of the data, and Fig. 5 summarizes the training workflow, the model results and the threshold logic. The model predicted appliance states with high accuracy, and the thresholds make the behaviour predictable: when the temperature rises from 26 °C to 30 °C the fan switches from OFF to ON, and when the light level drops from 500 to 120 the LED switches from OFF to ON.

Table 4: Random Forest performance on the test set

Metric	Value
Accuracy	96.2%
Precision (LED)	95.8%
Recall (LED)	95.6%
Precision (Fan)	94.7%
Recall (Fan)	94.3%

BODHIVRUKSHA JOURNAL OF DIVERSE DISCIPLINE
E-ISSN : 3139-1486
An Open Access, Peer-Reviewed, Multidisciplinary Scholarly Journal
Bi-monthly | Multilingual (English, Hindi, Marathi) | Academic Research
@ Volume 2, Issue 5 (September-October 2026) (Special Issue 1) ISSN: 3139-1486 (Online)

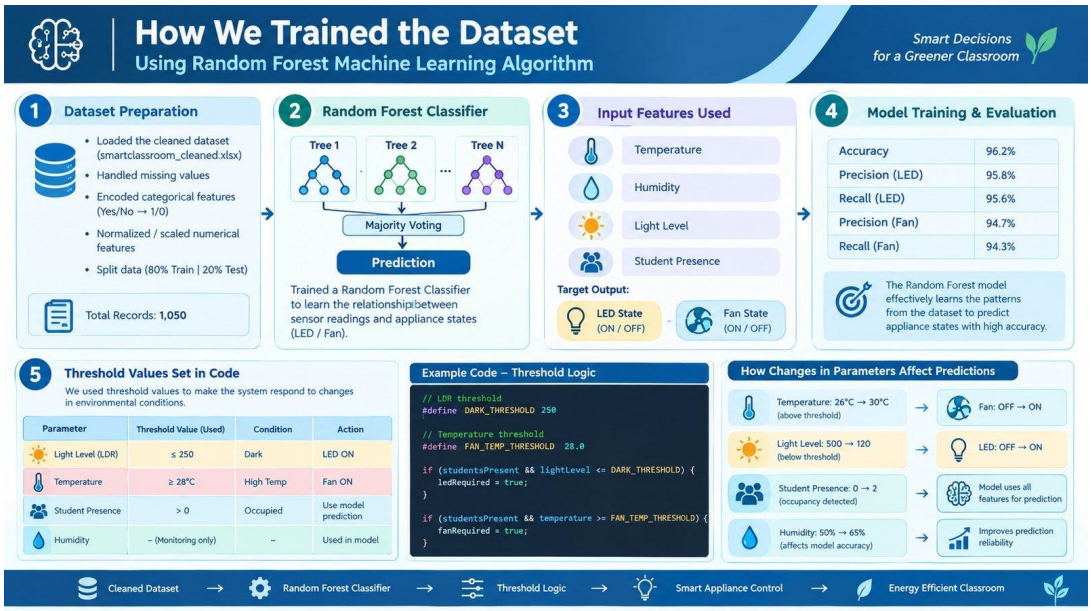


Fig. 5. Random Forest training workflow, performance summary and threshold logic.

D. Energy Saving and Cost

A plot of always-on classroom energy against AIoT-controlled energy for 9 AM to 2 PM points to a possible saving of about 40–60%. This figure comes from simulated and analysed data; it should be confirmed by metering, for example with the PZEM-004T, in a real classroom. The estimated cost of the prototype is about Rs. 1,960 (roughly Rs. 2,000), with the ESP32 board at Rs. 350, the DHT22 at Rs. 250, six IR modules at Rs. 240 and the 5 V adapter at Rs. 200 as the larger items; all prices are approximate market estimates.

Discussion

Applications. The system suits classrooms, laboratories, seminar halls and lecture theatres, and can extend to offices, meeting rooms, libraries and hostels, or to a whole campus for energy management and occupancy analytics.

Advantages. Lights and fans follow occupancy, light level and temperature, which cuts waste; the build is inexpensive and uses easily available parts; readings appear live on the OLED and are logged for analysis; threshold logic keeps the response predictable alongside a model with 96.2% test accuracy; IR sensing captures no images; and the modular design can take a dashboard, more sensors and more rooms.

Limitations. Because the prototype relies on a DC fan, an LED and a breadboard, it has neither been installed in a real room nor connected to mains loads. IR sensors report seat-level presence only and are sensitive to ambient light and mounting position. The 40–60% saving is an estimate and lacks long-term field data. With only 1,050 records, the model will probably need retraining for other rooms and seasons, and any air-conditioner or mains control calls for extra electrical safety measures.

BODHIVRUKSHA JOURNAL OF DIVERSE DISCIPLINE
E-ISSN : 3139-1486
An Open Access, Peer-Reviewed, Multidisciplinary Scholarly Journal
Bi-monthly | Multilingual (English, Hindi, Marathi) | Academic Research
@ Volume 2, Issue 5 (September-October 2026) (Special Issue 1) ISSN: 3139-1486 (Online)

Ethical, Societal and Sustainability Considerations

Logs of occupancy reveal how a space is used, so the system should keep only what it needs and limit who can open the logs and dashboards. IR sensing registers presence without recording images, which is gentler on privacy than cameras. A wrong prediction could leave an occupied room dark or hot, so a manual override must stay available and unusual events should be recorded.

Societal benefits include lower electricity use and operating cost, a comfortable learning space and data-driven facility decisions; possible drawbacks are over-reliance on automation, misuse of occupancy data and electronic waste from sensors and boards. Switching appliances off in empty or well-lit rooms lowers demand and the associated carbon footprint, and the low-power hardware could later be paired with solar power. The work aligns with SDG 7 (Affordable and Clean Energy), SDG 9 (Industry, Innovation and Infrastructure), SDG 11 (Sustainable Cities and Communities), SDG 12 (Responsible Consumption and Production) and SDG 13 (Climate Action).

Conclusion and Future Scope

This paper described an AIoT prototype in which IoT sensing, occupancy monitoring and machine learning together decide when a classroom's light and fan should run. The Random Forest scored 96.2% accuracy on test data, the circuit worked in simulation, and the prototype, costing roughly Rs. 1,960, was shown at the project exhibition. The literature shows that earlier work mostly handles prediction or monitoring separately, whereas this prototype joins occupancy sensing, ML-based decisions, automatic control, display and logging in one low-cost system.

Next steps are a web or mobile dashboard on the ESP32 Wi-Fi link, deep-learning models for sharper occupancy and energy prediction, extra sensing such as an MQ-135/CO_2 air-quality sensor, motion cameras or RFID, solar power for a fully sustainable room, and roll-out to several classrooms or a campus with PZEM-004T metering to confirm the real saving.

Acknowledgment

The authors thank their guide, Dr. Vishal Puranik, the Head of the Department, Bhagyashree Dhakulkar, and the Principal, Dr. F. B. Sayyad, for their guidance, encouragement and support, and all faculty members who offered technical help and feedback.

References

1. N. Nireekshana, "Data-driven power consumption assessment in educational institutions using machine learning techniques," J. Electr. Syst. Inf. Technol., vol. 13, 2026, doi: 10.1186/s43067-026-00389-z.
2. S. Wirayoga, N. Fairuzaman, M. M. Pratama, W. A. Fauzi, and M. A. F. Alfarizi, "Smart classroom 4.0 using embedded systems for attendance, energy monitoring, and environmental control," TELKOMNIKA, vol. 24, no. 3, 2026.
3. I. Firdaus et al., "Smart classroom monitoring system using IoT and AI to improve space utilization in higher education," J. Adv. Inf. Syst. Technol., vol. 7, no. 2, pp. 238--252, 2026, doi: 10.15294/jaist.v7i2.35430.
4. B. Tang, "Building-level energy prediction and control based on BIM and IIoT technologies," Sci. Rep., vol. 16, 2026, doi: 10.1038/s41598-026-51094-w.
5. I. Qaisar et al., "OCC-Mamba: A Mamba-based deep learning approach for indoor occupancy prediction," Build. Environ., vol. 289, p. 114085, 2026, doi: 10.1016/j.buildenv.2025.114085.

BODHIVRUKSHA JOURNAL OF DIVERSE DISCIPLINE
E-ISSN : 3139-1486
An Open Access, Peer-Reviewed, Multidisciplinary Scholarly Journal
Bi-monthly | Multilingual (English, Hindi, Marathi) | Academic Research
@ Volume 2, Issue 5 (September-October 2026) (Special Issue 1) ISSN: 3139-1486 (Online)

6. Z. Li, R. Shi, Q. Wang, Y. Chen, and T. Zhang, "Improving energy efficiency in university classrooms in China using vision-driven deep learning for real-time air conditioning control," J. Build. Eng., vol. 122, p. 115685, 2026, doi: 10.1016/j.jobe.2026.115685.
7. S. Zhang and C. Kong, "Deep learning and multi-objective optimization for real-time occupancy-based energy control in smart buildings," Sci. Rep., vol. 15, 2025, doi: 10.1038/s41598-025-23134-4.
8. B. S. Alotaibi, "Context-aware smart energy management system: A reinforcement learning and IoT-based framework for enhancing energy efficiency and thermal comfort in sustainable buildings," Energy Build., vol. 340, p. 115804, 2025, doi: 10.1016/j.enbuild.2025.115804.
9. S. H. Godasiaei, O. A. Ejohwomu, H. Zhong, and D. Booker, "Integrating experimental analysis and machine learning for enhancing energy efficiency and indoor air quality in educational buildings," Build. Environ., vol. 276, p. 112874, 2025, doi: 10.1016/j.buildenv.2025.112874.
10. L. Ortega-Díaz, C. A. Fajardo, and G. Osma-Pinto, "Performance of energy consumption prediction techniques in classrooms of an educational building in a warm tropical climate," Energy Build., vol. 344, p. 115967, 2025, doi: 10.1016/j.enbuild.2025.115967.
11. L. Ortega-Díaz, J. Jaramillo-Ibarra, and G. Osma-Pinto, "Estimation of the air conditioning energy consumption of a classroom using machine learning in a tropical climate," Front. Big Data, 2025, doi: 10.3389/fdata.2025.1520574.
12. N. Y. Ahmed, H. A. Illias, H. Mokhlis, N. N. Mansor, and M. Y. Ahmad, "Solar-powered smart monitoring system for occupancy and energy use in lecture rooms," J. Build. Eng., vol. 104, p. 112409, 2025, doi: 10.1016/j.jobe.2025.112409.
13. S. Y. Chin, K. Hasikin, N. S. M. Zaid, and A. A. Jamaludin, "Integrating behavioural and environmental data for energy forecasting in tropical campus buildings using machine learning techniques," J. Build. Eng., vol. 113, p. 114134, 2025, doi: 10.1016/j.jobe.2025.114134.
14. I. Chaer, B. Ozarisoy, M. A. E. Ismail, S. Salari, and Y. Zhihui, "Energy efficiency in educational buildings: A systematic review of smart technology integration and occupant behaviour," Build. Environ., vol. 280, p. 113132, 2025, doi: 10.1016/j.buildenv.2025.113132.
15. K. Elhabyb, A. Baina, M. Bellafkih, and A. F. Deifalla, "Machine learning algorithms for predicting energy consumption in educational buildings," Int. J. Energy Res., 2024, Art. no. 6812425, doi: 10.1155/2024/6812425.
16. R. Tariq, A. Mohammed, A. Alshibani, and M. S. Ramírez-Montoya, "Complex artificial intelligence models for energy sustainability in educational buildings," Sci. Rep., vol. 14, 2024, doi: 10.1038/s41598-024-65727-5.
17. F. Banihashemi et al., "Occupancy modeling on non-intrusive indoor environmental data through machine learning," Build. Environ., vol. 254, p. 111382, 2024, doi: 10.1016/j.buildenv.2024.111382.
18. M. N. Uddin et al., "Thermal and visual comforts of occupants for a naturally ventilated educational building in low-income economies: A machine learning approach," J. Build. Eng., vol. 94, p. 110015, 2024, doi: 10.1016/j.jobe.2024.110015.
19. L. Haifeng, H. C. Hou, and Z. Gou, "User-centric approach to optimizing thermal comfort in university classrooms: Utilizing computer vision and Q-XGBoost reinforcement learning," Energy Build., vol. 323, p. 114808, 2024, doi: 10.1016/j.enbuild.2024.114808.
20. J.-S. Chou and H.-M. Nguyen, "Simulating long-term energy consumption prediction in campus buildings through enhanced data augmentation and metaheuristic-optimized artificial intelligence," Energy Build., vol. 312, p. 114191, 2024, doi: 10.1016/j.enbuild.2024.114191.